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Optimization Tuning Model of Control Parameter Based on Artificial Immune Principle in Human Simulated Intelligent Controller

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Abstract

Parameter tuning is the puzzle in control engineering. Aimed at being difficult to make artificially the tuning which results in too many control parameters of intelligent controller, the paper presented a sort of optimization method of control parameters based on immunological principle. In the paper, it made the anatomy of the complexity and existing puzzles of control parameter tuning, presented the mathematical model of controller parameter tuning based on immune principle, gave the optimizing control algorithm of Clone selection. Taking a two-order process with time lag as an example, the control parameters of HSIC algorithm have been optimized by presented tuning model, made the comparative study with PID algorithm parameter optimized by other method, and the process simulation response demonstrated that the optimization tuning method based on immune principle could obtain the control performance and control quality better. Experimental study of simulation shows that it is reasonable and effective to the optimization method of control parameters presented in this paper.

***Keywords**: Control Parameters; Human Simulated Intelligent Controller; Immune Mechanism; Clone Selection; Mutation; Optimum Parameter*

1. Introduction

Control theory has undergone the development process from the classical, linear and the traditional to the modern, nonlinear and the large-scale system until the intelligent control theory. With the rapid development of control theory, there are many advanced control algorithms, but so far the parameter tuning design of control system controller is still the core content. In the optimization design of the controller, the two main puzzles needed to be solved are the selections of performance index and optimization based method [1]. The indexes of measuring a control system are 3 aspects of the stability, rapidity and accuracy. The rise time reflects the response speed of control process, the shorter the control time is, the better the control system quality is. In the practical application, if it is only the simple pursuit of system dynamic characteristics, then the control parameters obtained are likely to make the control signal be too large, and due to the inherent saturation characteristics in the system， it probably leads to the system instability. In order to obtain better control performance, generally, the rise time, process error and control amount are always viewed as the constraint conditions. In view of the fitness function with the associated objective function, the performance function that has been selected can be directly used as fitness function to optimize parameters.

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Consequently, under the condition of the constraints, the optimal parameter is the controller parameter corresponding to x when the performance function f (x) makes minimum. Inspired by artificial immune system [2-3], the paper put forward a sort of optimization tuning method of controller parameters based on immune mechanism. Experimental study of simulation demonstrated its effectiveness of the presented method to optimize the parameters of the controller.

2. Optimization Tuning Model of Controller Parameter

Table 1 shows the mapping relation between the body immune system and the immune based parameter tuning model [4]. In the randomly generated candidate solution, it can choose the advantage antibodies of greater affinity (smaller values) by means of the affinity calculation between antigen and antibody. In the cloning process, it retained the advantage gene, and made the advantage gene be mutated so as to generate a large number of new antibodies. Then, it makes a reevaluation for the new antibody set, and the new generation of antibody continuously updates the antibody set.

Table 1. Mapping Relation of Body Immune System and Immune Based Parameter Tuning Model

Body immune system	Immune based parameter tuning model
Antigen	Objective function
Antibody	Feasible solution
Cell clone	Antibody replication
Binding of Antibody and Antigen	Antigen value of antibody substituted into antigen
B cells, T cells	Vector
Increase of antibody concentration	Increase of approximate feasible solution

Updating mechanism of antibody is that the new generation of antibodies with higher affinity eliminates the antibodies with low affinity in the collection. The antibodies in antibody set arranges according to their affinity for ascending. Through the specified evolution generation, the optimal antibody can be extracted, thereupon then the optimal solution can be obtained.

2.1. Definition of Basic Concepts

In this paper, the problem of optimal solution and feasible solution is abstracted as antibody, and the definition of the relevant technical terms used in the algorithm is defined as follows.

Definition 1 Antigen refers to the objective function to be optimized.

Definition 2 Antibody refers to the candidate solution of the objective function. In the real number coding, the antibody is usually a multi-dimensional vector $X = \{ X_1, X_2, \cdots, X_n\}$, and each antibody can be expressed as a point in n-dimension space.

Definition 3 If the antibody is substituted into the antigen (the optimized objective function), and then the calculating value is called as antibody-antigen affinity.

2.2. Clone Selection Algorithm

In the human body immunity, when the antigen invades the immune system produces a large number of antibody to match the antigen. The concentration of antibody in antigen with high affinity will increase, and it is conducive to eliminate the antigen. When the antigen is crumbled, this kind of antibody produced will be inhibited. At the same time, the concentration of antibody will be reduced, and the immune system always maintains the immune balance. The advantage antibody which has high affinity with antigen is activated in the antibody collection [5]. In order to further eliminate the antigen and make a lot of cloning, the code of clone selection process is as follows.

```
Procedure Clone Select ()
Begin
Set antigen ag; /* s.t. min (J) */
Initialize randomly the antibody set;
    While (evolution generation < m) /*m is evolution generation */
    Begin
Calculating f affinity (ag, ab) of each antibody
            If reaching end condition, algorithm end
            Ascending order according to the affinity value
            Select the first θ antibody  according to f num (ab(i)) generating new antibody ab_new
            Mutate the produced new antibody ab new
            Randomly generated N new antibodies join to ab new
            While (ab new nonempty)
                Begin
                 Select the smallest cell affinity from antibody set;
              If (Selected the cell affinity large) then substitute by new antibody;
                End
    End
Output optimal solution from antibody set;
End
```

If the newly generated cells through clone selection process are merged into antibody set, then the antibody concentration will be increased, and it shows that the number of approximate solution is increasing. However, if the antibody is too concentrated and the concentration is too high, then it is hard to keep the diversity of antibody. The antibody with good evolutionary potential will be lost, thereupon it will fall into the local optimal.

This paper defines the number of memory cell clone in clone selection process.

$$f_{num} = \sum_{i=1}^{q} \left\lceil \frac{\beta \cdot \theta}{i} \right\rceil$$

in which, f_{num} is the clone number of all memory cells, the ith term represents clone number of ith cell, β is a preset parameter factor, and θ is the number of the advantage cells. From the expression, it can be seen that the greater the cell affinity is, the more the clone number is, and on the contrary, the less. For example, β = 2, θ = 100, the memory cell is ordered according to affinity size, therefore, the number of antibody cell clone of the affinity maximum is 200, the clone number is 100, and so on. At the same time, in order to avoid falling into local optimal, it introduces a certain amount of new antibodies generated randomly in the evolution process of each generation. Antibody cells are updated dynamically in the evolutionary process. Antibody cells are the optimal antibody selection from the current antibody and clone of new antibody. Thereby it can achieve the dynamic update of antibody cell set, and keep the antibody scale invariant.

2.3. Mutation

The aim of mutation is to make the sub-generation antibody coding changes so as to get the better solution than the parent generation. Since the antibody in the algorithm based on real coding, so the Gaussian mutation way is adopted, and the mutation does not act on the original population. In order to concentrate the search around the antibody with high affinity, at the same time, but also ensure the diversity of antibodies, this paper introduces an adaptive mutation operator, and that is the individual component of each mutation operator.

$$x_i = | x_i + Nm_i * N(0,1) * x_i |$$

in which, N(0,1) is a random number subjected to the standard Gauss distribution, | ·| shows calculating the absolute value, and Nm_i is the mutation rate of corresponding antibody which is defined as follows.

$$Nm_i = \rho \frac{f(x_i)}{max(f(x_i))}$$

Obviously, the antibody mutation rate is inversely proportional to its affinity, and the higher the affinity is, the smaller the mutation rate is. The antibody adaptively adjusts the mutation step according to the affinity value in each iteration process, it can make the search centralized around high affinity antibody so as to improve the convergence speed, and at the same time it can keep the population diversity. ρ is a mutation constant, it is used for adjusting the mutation strength, and it is related to the search space size and population scale.

3. Parameters Tuning of Controller

3.1. Objective Function

In order to obtain more satisfactory dynamic characteristics of the transition process, prevent the control energy being too large and avoid the overshoot in the optimization design of controller, it always adopts the performance index of error absolute value time integral as the minimum objective function of parameter selection, adds a square term of control input in the objective function, and applies the penalty function, namely once the overshoot emerges, the overshoot will be as a term of the optimal index. So, the optimal performance index of control parameter selection should be as follows.

$$J = \int_0^\infty (w_1 | e(t) | + w_2 u^2(t)) dt + w_3 \times t_u$$

$$if \quad e(t) < 0 \quad J = \int_0^\infty (w_1 | e(t) | + w_2 u^2(t) + w_4 | e(t) |) dt + w_3 \times t_u$$

in which, *e(t)* is the process error, *u(t)* is the controller output, t_u is the rise time, w_1, w_2, w_3 and w_4 are the weight values, and it satisfies $w_4 >> w_1$.

3.2. Controller Parameters

In order to compare the effect of controller parameter optimization, here it takes two sorts of controller as an example to discuss the parameter tuning method. The control process model is shown as Figure 1, in which, *r(t), e(t), u(t)* and *y(t)* are respectively the process input, process error, controller output and process output.

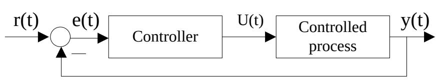

Figure 1. Control Process Model

（1）PID controller

With the rapid development of industrial automation, although PID algorithm being simple and strongly robust, the PID control technology is still the basis of industrial process control. The transfer function expression of control process is as follows.

$$W(s) = K_p (1 + 1/T_i s + T_d s)$$

in which, K_p, T_i and T_d are respectively the proportional coefficient, integral and differential constant.

In the actual application, it can adopt flexible combination of different control according to the characteristics of the controlled object and the requirements of control performance and proportion (P) controller, proportional integral (PI) controller and proportional integral differential (PID) controller.

（2）HISC controller

In the Figure 1, if the human simulated intelligent controller (HSIC) is adopted, by means of analyzing the relation between process error e and process error change rate $\dot{e}$, then it can constitute an error phase plane shown as Figure 2, and summarize up the error feature mode of control process. When the process error is located into the Ⅱ and Ⅳ quadrant, namely when $e \cdot \dot{e} < 0$ or $\dot{e} = 0$, then the process error will present the decreasing trend, and the error goes to zero gradually. When located into the Ⅰ and Ⅲ quadrant, namely when $e \cdot \dot{e} > 0$ or $e = 0$ and $\dot{e} \neq 0$, then the process error will present the increasing trend. Aimed at the two different modes of error feature, its corresponding control strategy is different. For the former, due to its automatic error decreasing trend, it can select the "keep" control pattern. The advantage of the control pattern is that it can eliminate the integral saturation and phase lag resulted in integral action without increasing the integral link. For the later, because the negative feedback proportional control can reduce the process error, it can select the proportional control pattern.

In order to achieve better control performance, according to the different e and $\dot{e}$ the error phase plane can be divided into different control region symmetry, and it is shown as Figure 2. For example, e can be set in advance for the two thresholds, *Abs (*e_1*)>Abs (*e_2*)*, and $\dot{e}$ is set as a threshold Abs ($\dot{e}_1$), and then the error phase plane can be divided into 6 control areas. According to the error feature mode of different regions, it can adopt different control strategies, and thereby construct the control algorithm of different error feature modes.

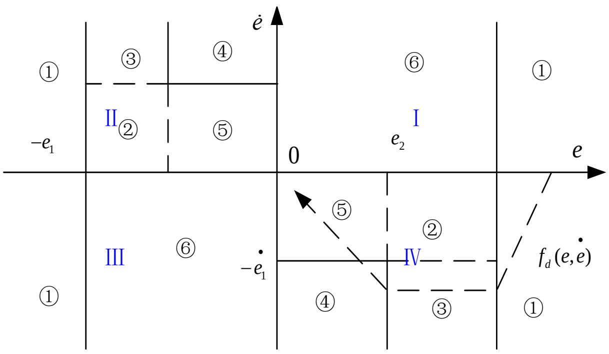

Figure 2. Error Phase Plane

① If Abs (e)≥Abs(e_1), aiming at the characteristic of process error e being large, no matter how to determine the process error change rate $\dot{e}$, in order to decrease process error, the Bang-Bang control strategy is the best choice because it can most rapidly reduce process error.

② If $e \cdot \dot{e} < 0$, Abs ($\dot{e}$)≯Abs ($\dot{e}_1$), because the process error e is reducing, the proportional control pattern is desirable. Due to the differential control being added, it can accelerate the change of process error change rate $\dot{e}$, so it can select proportional plus derivative control strategy.

③ If $e \cdot \dot{e} > 0$, Abs (e)<Abs (e_1), Abs ($\dot{e}$) can be taken as arbitrary value because of the same reason as case ②, where the proportional plus derivative control strategy is more preferable.

④ If $e \bullet \dot{e} < 0$, but Abs ($\dot{e}$) > Abs ($\dot{e}_1$), in order accelerate the change of process error change rate $\dot{e}$, the proportional feedback plus derivative control strategy is more selectable.

⑤ If $e \bullet \dot{e} < 0$, Abs (e) < Abs (e_2), Abs ($\dot{e}$) < Abs ($\dot{e}_1$), under the condition of all e and $\dot{e}$ achieving the expected value, in order to eliminate the steady state error of process control, the proportional plus integral control strategy can be used.

Through the above analysis, the control algorithm based on human simulated intelligent control (HSIC) can be summarized up as the following.

$$u_n = \begin{cases} \operatorname{sgn}(e_n)U_{\max} & (Abs(\mathrm{e}) \geq Abs(\mathrm{e}_1)) \\ K_p \cdot e_n & (Abs(\dot{e}) \geq Abs(\dot{e}_1)) \\ K_p \cdot e_n + K_d \cdot \dot{e}_n & (Abs(\dot{e}) \geq Abs(\dot{e}_1), Abs(\mathrm{e}) \geq Abs(\mathrm{e}_2)) \\ -K_p^{'} \cdot e_n + K_d^{'} \cdot \dot{e}_n & (Abs(\dot{e}) \geq Abs(\dot{e}_1), Abs(\mathrm{e}) \leq Abs(\mathrm{e}_2)) \\ -K_p \cdot e_n + K_i \cdot \sum_{i=1}^{n} e_{m,i} & (Abs(\dot{e}) \leq Abs(\dot{e}_1), Abs(\mathrm{e}) \leq Abs(\mathrm{e}_2)) \end{cases}$$

in which, e_n is the nth process error, $e_{m,i}$ is the ith extremum of process error, $\dot{e}_n$ is the change rate of the nth process error, u_n is the nth output of controller. $U_{\max}$ is the maximum of controller output, $K_d, K_d^{'}$ are the differential coefficients, $K_p, K_p^{'}$ are the proportional coefficients, and K_i is the integral coefficient.

4. Simulation Experiment and Its Analysis

4.1. Simulation Experiment

In order to verify the outstanding performance of optimization tuning algorithm of controller parameters based on immune mechanism, here the paper takes the process control with large time lag as an example, it makes the simulation experiment to the same controlled object respectively by the traditional PID control algorithm and controller parameter tuning algorithm of IHSIC based on immunological principle, and compares the response results of PID control method respectively tuned by Chien Hrones Reswick (CHR)Refined Ziegler Nichols (RZN) and Genetic Programming with ZN (GP) [6-9].

It is assumed that the transfer function model of the controlled object is as W (s) = $e^{-5s}/(1+s)^2$.

By means of using real number coding method, the antibody coding of control parameters which need to be optimized is $K_p, K_p^{'}, K_d, K_d^{'}$, e_1, e_2, $\dot{e}_1$, the parameter range of $K_p, K_p^{'}$ is over interval [0, 30], the parameter range of $K_d, K_d^{'}$, K_i is over interval [0, 5], the antibodies are set to be the 100 generation of the evolution generation, the population size is set to be 50, the range of $e_1, e_2, \dot{e}_1$ is over interval [0, 1]. It takes $w_1 = 0.999$, $w_2 = 0.001$, $w_4 = 100$, $w_3 = 2.0$, $\theta = 20$, $\beta = 5$, and in every evolution generation, it increases 5 antibodies randomly so as to improve the ability of global optimization. The adopted optimal performance index of control process has been discussed in the 3.1section of this paper, and here omitted.

Under the precondition of the above assumption, the parameter comparison of the obtained optimal control parameters is shown as in Table 2 by different tuning methods, and the response curve of different optimal control parameters is shown as in Figure 3.

Table 2. Optimal Control Parameter by Different Tuning Methods

Parameters and variables	IHSIC	GP	RZN	CHR
Kp	$K_p, K_p^{'}, K_d, K_d^{'}, K_i,$ $e_1, e_2, \dot{e}_1^*$	0.49	0.15	0.49
Ti		3.56	2.02	3.67
Td		0.99	0.38	2.48

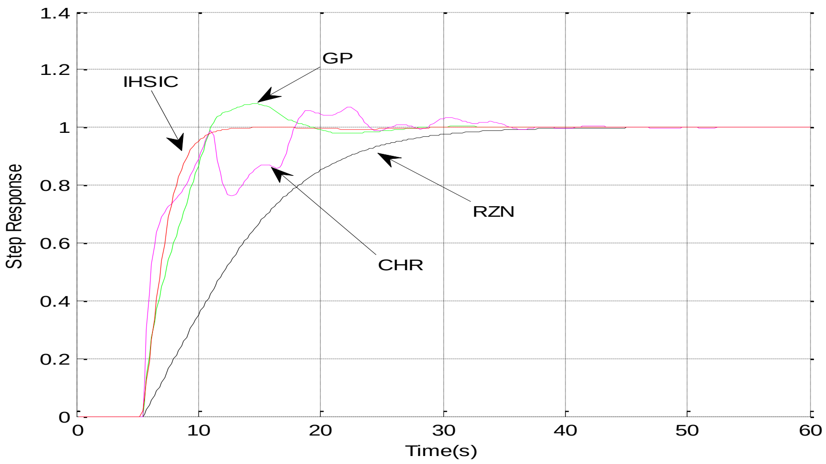

Figure 3. Comparison Curve of Simulation by Different Tuning Method

4.2. Experiment Analysis

From the Tab.2 and the Figure 3 it can be seen that the parameter tuning method of IHSIC outperforms the others in all respects of rise time and transition process time, there is no overshoot, and it obtained more ideal control effect. The main reason is that the tuning method of IHSIC is a kind of multi-modal control method based on human simulated intelligent control, and it can design the control pattern according to the requirements of control quality. The parameter tuning method of IHSIC based on immune principle can obtain the optimal control parameter under the optimal performance index J, because it adopts the cloning mechanism according to the affinity level. Therefore, it can effectively guide "explore" to be concentrated in the better solutions of the neighborhood, and the greater the affinity is, the more the antibody clone quantity is, the more conductive the optimal solution finds. Due to adopt the adaptive mutation strategy, it can automatically adjust the mutation step length, make the search centralized around the antibody with high affinity, maintain the diversity of the population, and further enhance the ability of finding optimal solution. The new antibody added randomly can effectively avoid the algorithm to fall into a local optimum, and therefore, it can obtain the global optimal solution, or at least the sub-optimal solution.

5. Conclusions

The above explored the clone selection algorithm based on the immune principle, set up the mathematical model of controller parameter tuning, gave the definition of antigen, antibody and affinity in parameter tuning model, and made a detailed description in controller parameter based on the principle of immune tuning process. It took the parameter tuning in PID and HSIC controller as an example, the simulation experiment validated the effectiveness of the proposed method. The contrastive analysis shows that the presented method owns very good control quality, it provides a new method of controller parameter tuning, and has the reference significance to the research and application generalization of control theory.

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